

BANA 4090: Chapter 5: (Part I)

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- Main topics:
 - o HW # 4
 - Exponential smoothing

HW # 4

Forecast errors

- Forecast "error": the difference between an observed value and its forecast:
 - $\circ\ e_{T+h} = y_{T+h} \hat{y}_{T+h|T}$,where the training data is given by $\{y_1,\ldots,y_T\}$.
- R Lab Notes (selecting values from a matrix in R).

Exponential smoothing

Exponential smoothing

- What it is?
- Exponential smoothing methods are...
 - weighted averages of past observations, with the weights decaying exponentially as the observations get older.

Types of exponential smoothing

- What are the 3 main types of exponential smoothing?
 - Simple exponential smoothing: for series with no trend or seasonality.
 - Holt's method: with trend, no seasonality.
 - Holt-Winter's method: with trend & seasonality.

Exponential smoothing

Big picture

- Forecast future values using a weighted average of all previous values in the series.
- Advantages:
 - flexible,
 - computationally efficient,
 - good performance, ease of automation,
 - ease of automation.

A specifical case: Moving average

- The idea: Compute value based on average of several observed values.
- **Uses**: Visualization, Forecasting, Computing seasonal indices.
- Advantages: Simple, intuitive, popular, data-driven.
- **Key concept**: Width of window.
- Trailing moving average(trailing MA): based on a window from time t and backwards. In R, ma() function.
 - To forecast a series at time t+k, use a trailing MA that ends at time t.

Data Example

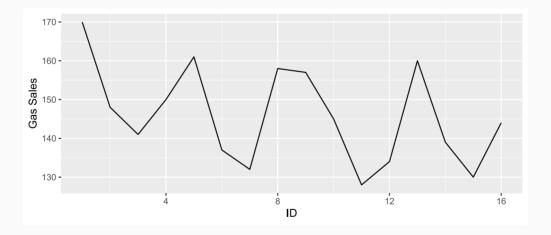
- Using the Natural Gas Sales.xls data:
 - Identify the preferred window length for moving average
 - Compute and plot a centered moving average
 - Remove the last observation (Fall 2004) and use a trailing MA to predict for Fall -2004
 - How does this prediction compare to a seasonal naive estimate?

• Import data:

```
## # A tibble: 8 x 2
   Quarter `Gas Sales`
###
    <chr>
                     <dbl>
##
## 1 Winter-2001
                       170
## 2 Spring-2001
                 148
## 3 Summer-2001
                  141
## 4 Fall-2001
                      150
## 5 Winter-2002
                       161
## 6 Spring-2002
                 137
## 7 Summer-2002
                       132
## 8 Fall-2002
                       158
```

- Plot so that we can identify preferred window length.
- Seasonality appears to follow the quarters so an appropriate window length would be 4.

```
gas %>%
  mutate(ID = 1:nrow(gas)) %>%
  ggplot(aes(ID, `Gas Sales`, group = 1)) +
  geom_line()
```

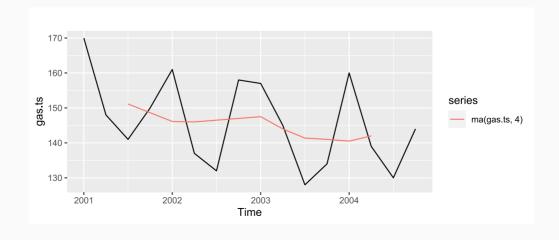


• Convert to a time series object:

```
gas.ts \leftarrow ts(gas[2], start = c(2001, 1), frequency = 4)
gas.ts
       Qtr1 Qtr2 Qtr3 Qtr4
##
## 2001
        170
             148
                  141
                       150
## 2002
        161
             137
                  132
                       158
## 2003 157
             145
                  128 134
## 2004
        160
             139
                  130 144
```

• Compute and plot a moving average:

```
ma(gas.ts, 4)
##
          Qtr1
                 Qtr2
                         Qtr3
                                   Qtr4
## 2001
             NA
                     NA 151.125 148.625
  2002 146.125 146.000 146.500 147.000
  2003 147.500 144.000 141.375 141.000
## 2004 140.500 142.000
                             NA
                                     NA
autoplot(gas.ts) +
  autolayer(ma(gas.ts, 4))
```



• Partition data to remove the last observation as test data:

```
train \leftarrow window(gas.ts, start = c(2001, 1), end = c(2004, 3))
train
       Qtr1 Qtr2 Qtr3 Qtr4
###
        170
             148
                  141
## 2001
                       150
## 2002
        161
             137 132
                       158
## 2003 157
             145 128 134
## 2004 160 139 130
test \leftarrow window(gas.ts, start = c(2004, 4), end = c(2004, 4))
test
##
        Qtr4
## 2004 144
```

• Use trailing MA to predict Fall 2004:

```
ma ← forecast(rollmean(train, 4, align = "right"), h = 1)
ma

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
## 2004 Q4 140.7499 137.5859 143.9139 135.911 145.5889
```

• Use seasonal naive model to predict Fall 2004:

```
sn ← snaive(train, 1)
sn

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
## 2004 Q4 134 121.3723 146.6277 114.6875 153.3125
```

• Compare the accuracy of the two methods:

```
accuracy(ma, test)
###
                      ME
                            RMSE
                                     MAE
                                                MPE
                                                       MAPE
                                                                MASE
## Training set -0.9554378 2.358523 1.836250 -0.6658609 1.269043 0.4052414
## Test set 3.2500524 3.250052 3.250052 2.2569808 2.256981 0.7172529
##
                    ACF1
## Training set -0.1962972
## Test set
                      NΑ
accuracy(sn, test)
                            RMSE MAE MPE
###
                     ME
                                                 MAPE MASE ACF1
## Training set -4.181818 9.853472 8 -3.122110 5.666473 1.00 -0.1788168
## Test set
              10.000000 10.000000 10 6.944444 6.944444 1.25
                                                                  NA
```